

A distributed cellular automata model to simulate potential future impacts of climate change on snow cover area

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ABSTRACT

Snow dynamics in alpine systems play an important role in water resources management. One of the main variables that characterises the snowpack is snow cover area. In this paper, we present a novel methodology to assess the impact of climate change scenarios on snow cover area in alpine systems. The methodology calibrates and validates a distributed cellular automata (CA) model. Potential climate change scenarios can be generated to feed the CA model in order to assess the potential impact of climate change on snow cover area. The methodology has been applied to the Sierra Nevada mountain range in southern Spain, an area with a Mediterranean climate, which is valuable in terms of both its ecology and the tourism industry. Snow falls on the mountains from October to May, but this snow season may vary in the future due to climate change. We analysed the influence of elevation on the potential impact of climate change on the area covered by snow. The size of the potential changes associated with climate change increase with elevation in the case of temperature and decrease in the case of precipitation. These potential changes will modify snow dynamics, causing an important reduction in the area covered by snow (mean 60.4%) for the future horizon considered (2071–2100).

1. Introduction

Climate change will modify the availability of water resources in the future (Arnell and Lloyd-Hughes, 2013; Pulido-Velazquez et al., 2017). Alpine systems where the majority of precipitation is solid could be very sensitive to climate change (Horton et al., 2006; Gobiet et al., 2014). Snow dynamics govern ecosystems and so any variation in snow availability could bring significant changes to these ecosystems (Beniston 2003; Edwards et al., 2007). From the point of view of water resources, an assessment of the impact of future potential climate change scenarios on snow is essential for appropriate water resources management (Barnett et al., 2005; Arnell and Lloyd-Hughes, 2013). Accordingly, assessments of snow cover area (SCA) and potential changes to it become key to assessing climate change in alpine systems.

SCA is one of the main variables that characterises the snow dynamic, which is important for assessing water resources and their management. Snow Water Equivalent (SWE) quantifies the availability of water in the snow pack; if we want to obtain the SWE in a certain area we need to estimate snow depth and the snow density in the domain with snow, which is defined by the snow cover area (SCA).

Several studies have been done to estimate snow depth using snow stakes (e.g., Kucerova and Jenicek, 2014; Collados-Lara et al., 2017) and

snow density (e.g., Lopez-Moreno et al., 2013; Bormann et al., 2013). With regard to SCA, various agencies have developed products to estimate SCA based on satellite data (e.g., Rutgers University Global Snow Lab, which uses NOAA satellite data; NASA Distributed Active Archive Centre, which uses MODIS satellite data), but sometimes we need information that covers a longer period or with higher spatiotemporal resolution to assess operational issues. Where such remote-sensing data is available, SCA estimates can be directly used as input for hydrological models (e.g., Thirel et al., 2013; Mir et al., 2015). Elsewhere, however, SCA data may be unavailable, or have too crude a spatial resolution to assess the operational issues in question. Moreover, satellite data may be useless during certain periods if cloud cover obscures the view or if there has been a sensor failure (Ackerman et al., 1998; Schmugge et al., 2002). In such cases, alternative tools or models are required to estimate SCA.

To date, SCA has been analysed using various procedures, including physically-based models (Molotch et al., 2004; Warscher et al., 2013), regression techniques (Richer et al., 2013; Mir et al., 2015), artificial neural networks (Hou and Huang, 2014; Mishra et al., 2014) and cellular automata (CA) models (Leguizamón, 2006; Pardo-Igúzquiza et al., 2017).

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Cellular Automata (CA) are infinite, regular lattices of simple finite state machines that change their states synchronously, according to a local update rule that specifies the new state of each cell based on the former states of its neighbours (Wolfram, 1984; Kari, 2005). CA models were first described by Wolfram (1983) to simulate complex dynamics using simple rules of interaction between cells that discretize the area of interest. In this paper we apply CA models to the field of hydrology, and in particular the role of SCA in water resources availability, since CA models are capable of capturing the dynamics of SCA. Moreover, there is great potential for using calibrated and validated CA models to estimate SCA in periods where no SCA data are available. Nevertheless, to date few studies have addressed this issue. Leguizamón (2006) undertook a preliminary study, though this involved significant limitations. These limitations were pinpointed and overcome by Pardo-Igúzquiza et al. (2017) in a study that extended the idea of using CA models to estimate SCA. They proposed a novel algorithm to estimate SCA based on the state of the cell during the previous time step, the states of a given configuration of neighbouring cells at the previous time step, and a set of transition rules. These transition rules involve unique precipitation (P) and temperature (T) indices (driving variables) for the entire mountain range. Classic CA models do not require driving variables but they are needed in order to simulate realistic snow dynamics (Pardo-Igúzquiza et al., 2017).

The climatic indices of the aforementioned CA models can be defined using potential future climatic scenarios of precipitation and temperature in order to assess potential future impacts on the target variable.

Potential scenarios of precipitation and temperature can be obtained using statistical correction techniques applied to simulations performed using different Regional Climatic Models (RCM) (Chen et al., 2013, 2014). These models have spatial resolutions of tens of kilometres and they are nested inside General Circulation Models (GCM) with spatial resolutions of hundreds of kilometres. Generally RCMs cannot be applied directly to assess climate change because they show significant bias with respect to historical time series (Cook et al., 2008; Seager et al., 2008). Appropriate corrections are required to analyse the potential impacts of climate change in a particular system (Collados-Lara et al., 2018). Statistical corrections can be applied using one of two conceptual approaches (bias correction or delta change) depending on the series used to perform the transformation function (Räty et al., 2014; Sunyer et al., 2015). Bias correction approaches apply a correction to the control simulations of RCM in order to fit them to a historical series; then they assume the same biases for the future period in question (e.g., Piani et al., 2010; Watanabe et al., 2012).

Meanwhile, delta change approaches assume that the difference between control and future simulations of RCM are valid, and then use these differences (deltas) to correct the historical series in order to obtain potential future scenarios (e.g., Pulido-Velazquez et al., 2011, 2015; Räisänen and Räty, 2012).

In this paper, we propose a systematic methodology to estimate SCA dynamics in alpine systems that contains two new innovations: (1) the development of a spatially distributed CA model (for driving variables and parameters) to estimate SCA and (2) the use of the calibrated distributed CA model to assess the impacts of potential climate change scenarios on snowpack. To achieve this, we have extended the algorithm proposed by Pardo-Igúzquiza et al. (2017) to obtain a distributed approach with spatially distributed climatic indexes and spatially distributed parameters. We test different approaches to search for the optimal parameters and use spatially distributed indices to calibrate the CA algorithm. The calibrated CA models can then be fed with future potential precipitation and temperature scenarios in order to assess the expected changes in SCA.

The proposed methodology is applied to a Mediterranean alpine system where changes due to climate change are expected to be significant; however the method is general and could be applied to any alpine system for different purposes. The assessment of spatial and quantity changes in SCA are crucial to water resources management and ecosys-

tem impact assessments (Beniston 2003; Edwards et al., 2007). Thus, this tool has great potential to be used in operational environmental management due to its ability to estimate and predict the potential impacts of climate change on SCA. On the other hand, this tool could be useful to meteorological forecasts in alpine systems since albedo is an important variable in numerical weather prediction models and is closely related to SCA (Yucel, 2006; Moody et al., 2008).

2. Methodology

In this work we propose a method for performing a sensitivity analysis of the SCA dynamic in potential future climate scenarios, assuming steady land use/land cover (LULC) in the historical and future scenarios. It is based on the CA model developed by Pardo-Igúzquiza et al. (2017), which uses five parameters and two driving variables (P and T) to estimate SCA. This relatively simple approach can be used in cases where daily SCA, precipitation and temperature data are available for calibration, but where only precipitation and temperature are available in the operational mode. The model estimates SCA as one of two possible binary states in each cell: snow cover represented by 1 or no snow cover represented by 0. It uses a set of interaction rules that involve the parameters, driving variables (precipitation (P), temperature (T) and elevation (H)), and approaches to the interaction between neighbouring cells. The parameters to be calibrated in this CA model are: P_0 is a precipitation threshold; a and b are the intercept and the slope that define the straight line that represents the discretized snowline (the altitude above which the terrain can have snow); T_c is a temperature threshold; and N_m is the threshold in the number of neighbour cells that produce a change in the cell state. In this study we propose calibrating the parameters in a distributed fashion in accordance with some climatic zones. They are areas in which we assume homogeneous climate conditions (P and T) and parameters of the CA model. Those climatic zones (k) are discretized in cells (i, j) to perform simulations with the objective of determining the state of the cell (0 if it is free of snow and 1 if it is covered by snow) following the below transition rules:

- (1) If $P(k, t) \geq P_0(k)$ and $H(i, j) > H_s(k, t)$ then $S(i, j, t) = 1$
- (2) If $P(k, t) < P_0(k)$
 - a. If $T(k, t) - T(k, t-1) \leq T_c(k) > 0$ then $S(i, j, t) = S(i, j, t-1)$
 - b. If $T(k, t) - T(k, t-1) > T_c(k) > 0$ then
 - I. If $S(i, j, t-1) = 0$ then $S(i, j, t) = 0$
 - II. If $S(i, j, t-1) = 1$ then
 - i. If $N(i, j, t) \leq N_m(k)$ then $S(i, j, t) = 0$
 - ii. If $N(i, j, t) > N_m(k)$ then $S(i, j, t) = 1$

where $H_s(k, t)$ is the elevation of the snowline for climatic zone k and day t defined as $H_s(k, t) = a(k) + b(k) \cdot T(k, t)$, and $N(i, j, t)$ is the number of neighbour cells with $S(i, j, t-1) = 1$, considering a neighbourhood of 24 cells in which all the cells are close enough to have the same influence on cell state.

Note that rules a. and b. could be replaced by more global rules in order to have a more physical explanation, as follows:

- a'. If $T(k, t) \leq T_c(k) > 0$ then $S(i, j, t) = S(i, j, t-1)$
- b'. If $T(k, t) > T_c(k) > 0$ then
 - I. If $S(i, j, t-1) = 0$ then $S(i, j, t) = 0$
 - II. If $S(i, j, t-1) = 1$ then
 - i. If $N(i, j, t) \leq N_m(k)$ then $S(i, j, t) = 0$
 - ii. If $N(i, j, t) > N_m(k)$ then $S(i, j, t) = 1$

The main rule that defines the accumulation of snow in the CA model depends on the precipitation threshold and the snowline. The snowline is the altitude above which the terrain can have snow and it is approached by a straight line defined by parameters a and b and the temperature. It varies with the time and the climatic zone. If the elevation of a cell is above the snowline elevation and precipitation is sufficient, the state of the cell will be 1 (snow covered). The other two parameters, T_c and N_m are related to the snow melt processes, when a

pixel at state 1 changes to state 0. A higher temperature with respect to the previous day (rules a. and b.) or with respect to the global threshold (rules a'. and b'.) are related to snowmelt. In the same way, a lower number of neighbour cells with snow is also related to snowmelt. That is, a large number of neighbour cells with snow imply more inertia in the cell to continue with the same state (*i.e.*, with snow), while a small number of neighbour cells with snow implies that the cell is close to the border of the snowpack and has less inertia to change to the non-snow state.

In the model proposed by Pardo-Igúzquiza et al. (2017) the search for the parameters' optimal values in the calibration phase is done by varying one parameter and leaving the remaining ones fixed. In this study, we have modified the algorithm to vary all parameters simultaneously. An initial range of three values for each parameter is defined; then the ranges of all parameters are moved simultaneously until the optimal value is located in the middle of the range. The set of values yielding the minimum mean squared error (MSE) between the experimental and simulated SCA for the calibration period are chosen as the best parameters.

CA models are distributed if the driving variables and parameters are distributed spatially, or lumped if unique indices and parameters are used for the entire mountain range. In order to test distributed approaches, the calibration of a previous lumped CA model is used as a 'first iteration', to identify and select the best driving variables and define the 'set-up' or initial values of parameters for the distributed case. The numerical experiment that uses lumped series and parameters allows several driving variables and parameters to be tested simultaneously and, due to its low computational cost, saves time compared to setting up the distributed case from zero; the optimal parameters for the lumped case provide an idea of the interval ranges to be used in the distributed case. For the distributed cases, climatic indices (P and T) can be defined over a grid containing different climatic zones. This grid can have a resolution that is the same or coarser than the SCA grid. A semi-distributed case can be developed if we use distributed climatic indices and lumped parameters. The computational cost of distributed approaches depends on the resolution of the grids. If a fine calculation grid is chosen in which several climatic zones are defined, the search for optimal parameters can be done in two phases in order to avoid excessive calculation times for the algorithm. Some parameters can be fixed in the first phase according the results of the lumped case, then varied in the second phase. Different distributed variants can be tested with respect to the driving variables (the climatic indices of each climatic zone can be used as driving variables for that climatic zone or for the whole mountain range) and the domain of minimization (parameters can be calibrated by minimising the MSE for each climatic zone in the entire mountain range). These different configurations need to be tested for each case study in order to find the best results in the calibration and validation phases.

With respect to the uncertainties of the CA model, it should be noted that the architecture of the CA is not probabilistic and thus it is impossible to evaluate the intrinsic uncertainty of the model. This uncertainty can be decreased by improving the approach provided in the initial CA model. Uncertainty in the parameters could be evaluated by considering the following assumptions:

- 1) The calibration process, where the mean square error is minimised, can be seen as a least squares estimation procedure.
- 2) The parameters are going to be considered as a set of joint Gaussian variables.
- 3) Given (2), the estimation procedure in (1) is equivalent to the maximum likelihood estimation.
- 4) An approximate variance-covariance matrix (C), assuming a Gaussian distribution of the parameters, is estimated by standard nonlinear inversion theory (Menke, 1984):

$$C \approx [J^T \cdot \Gamma^{-1} \cdot J]^{-1} \quad (1)$$

where J is the Jacobian or sensitivity matrix evaluated at the generalised least square estimates and Γ is the identity matrix multiplied by the MSE in the validation period. On the other hand, the uncertainty of the CA model outputs can be quantified by considering the MSE of the calibration period to be the variance in the validation period. This procedure allows for a representation of the uncertainty interval [SCA estimate $-\sigma$, SCA estimate $+\sigma$] for the validation period and for a comparison of the number of days with experimental data within this interval to the theoretical value, assuming a Gaussian distribution (68%).

The CA model presented in this study only considers three driving variables: elevation, which can be considered constant for the temporal scale used in hydrological studies, and precipitation and temperature, which can be varied in accordance with climate change scenarios. Calibrated CA models allow the impact of potential climate change scenarios on SCA to be assessed using the future series generated for the driving variables selected. Also, if we consider distributed CA models, the spatial variation of climate change can be incorporated into the study. Note that the CA model presented is only able to assess the potential impacts of climate change due to precipitation and temperature. RCMs have significant bias with respect to the historical series. Statistical correction techniques (*e.g.*, first moment correction, second moment correction, regression, quantile mapping) can be used to reduce this bias. Bias correction and delta change correction techniques can be applied to the RCM to obtain the future precipitation and temperature series.

In this study we apply both bias and delta change approaches. The second moment correction technique is used in both cases. This technique corrects both mean and standard deviation to define the transformation function. We applied the transformation function proposed by Pulido-Velazquez et al. (2011) for the delta change method. Ensembles of the future series are proposed to obtain more representative potential future climate scenarios. We used equi-feasible solutions (considering all RCM simulations) for the bias correction and delta change methods.

The future precipitation and temperature series generated were used as input for the selected distributed CA model (previously calibrated) to assess the potential changes in SCA.

3. Application to the case study and data employed

3.1. Case study

Our case study is the Sierra Nevada mountain range in southern Spain (see Fig. 1A). It extends over 80 km, is between 15 and 30 km wide and covers more than 2000 km². It includes the highest point on the Iberian Peninsula – Mulhacén Peak, which is 3478.6 m a.s.l. The Sierra Nevada enjoys a high-mountain Mediterranean climate with relatively dry summers, and wetter winters, during which the majority of precipitation falls as snow. Thus, snowfall dynamics are essential to the availability of water in the Sierra Nevada catchments. The study of these dynamics and future potential changes in SCA is a key issue for the region from the point of view of the ski industry, which is an important economic driver, but also from a water resources standpoint. This study proposes a new methodology than could provide useful knowledge about the future impacts of climate change on sensitive, high-altitude landscapes, such as in this case of the alpine mountains of the Spanish Sierra Nevada. In our case study, LULC changes in the historical period employed for the calibration are not very significant. Note that the area of interest in this study is an alpine area where forest canopy is scarce (Fig. 1B). Assessing SCA dynamics in forested areas is more difficult due to the interaction between snow and vegetation and therefore it would be necessary to assess the suitability of the proposed method in these cases (see Section 4).

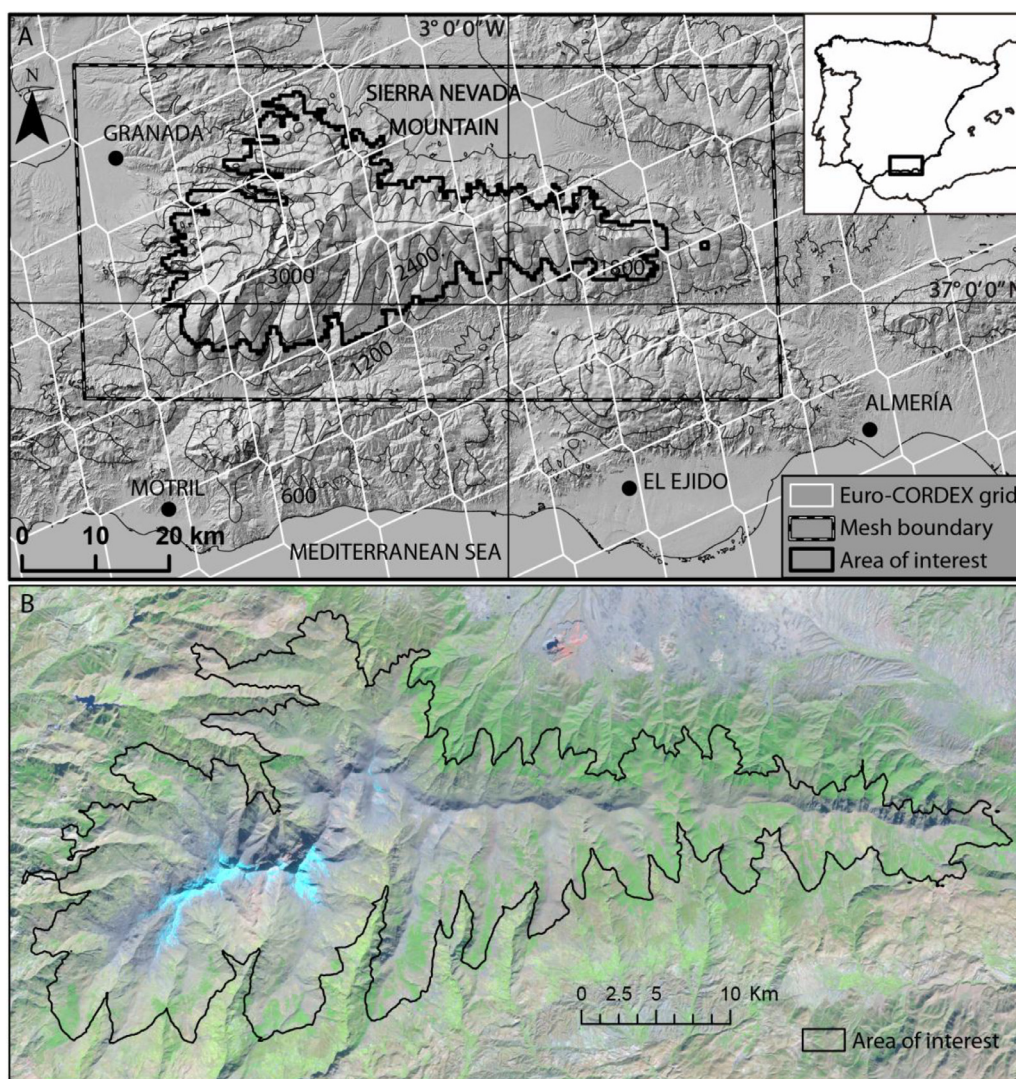


Fig. 1. A) Location of the study area. B) Land cover of the area of interest (Day image from 01/11/1999 from the Landsat 7 satellite).

3.2. Application to the case study

The CA model considered requires an input of SCA data, which can be collected from satellite images. In our case study, the experimental SCA data were taken from a MODIS satellite product. We used the MODIS/Terra Snow Cover Daily Global 500 m Grid (Data Set ID: MOD10A1), which has a spatial resolution of approximately 460 m for the latitude of the study area and a temporal resolution of 1 day. The SCA data were transformed to binary codes (1 = covered by snow; 0 = snow-free). The grid used by this product was also used for the calculations. There are around 4100 cells in a 460 m × 460 m grid inside the area of interest (Fig. 1).

The CA model also requires climatic indices (P and T) as driving variables. These were obtained from the Spain02 project dataset (Herrera et al., 2012, 2016). The Spain02 dataset contains daily temperature (maximum, mean and minimum) and precipitation estimates from historical data (around 2500 monitoring stations) collected by the Spanish Meteorological Agency over the period 1971–2010. We used version 4 (v4) of the Spain02 project dataset (<http://www.meteo.unican.es/en/datasets/spain02>), which includes daily field estimates with a spatial resolution of approximately 12.5 km using the Euro-CORDEX grid. In the case study, we have defined the climatic zones (introduced in the previous section) using the

Euro-CORDEX grid (see Fig. 1). The parameters and driving variables depend on the climatic zones in the distributed cases.

We applied the modified algorithm (varying the parameters simultaneously) to a three-year timespan (the calibration period was 1 July 2000 to 30 June 2003, whilst the validation period was 1 July 2003 to 30 June 2006). We have selected these periods due to the availability of data, but a comparison between different periods could be useful in order to assess the impact of selecting adjacent years.

For the case study we have tested different numerical experiments (approaches) with respect to the spatial distribution of driving variables and parameters (lumped or distributed), the tested variables (different variables and elevation thresholds), the calibration procedure (minimization of error and searching for optimal parameters) and temperature threshold (global or linked to the previous day). All of these numerical experiments are summarised in the following lines.

As a first approach, we tested lumped driving variables (mean precipitation, and maximum, mean and minimum temperatures above 1000, 1500, 2000, 2500 and 3000 m a.s.l.) [numerical experiment A1]. Fig. 2 shows the MSE for the various combinations of elevations and variables.

From numerical experiment A1, we selected precipitation and maximum temperature above 1000 m as the driving variables. Better approximations were obtained – in the sense that a smaller MSE was achieved – than for numerical experiment AA (performed by Pardo-

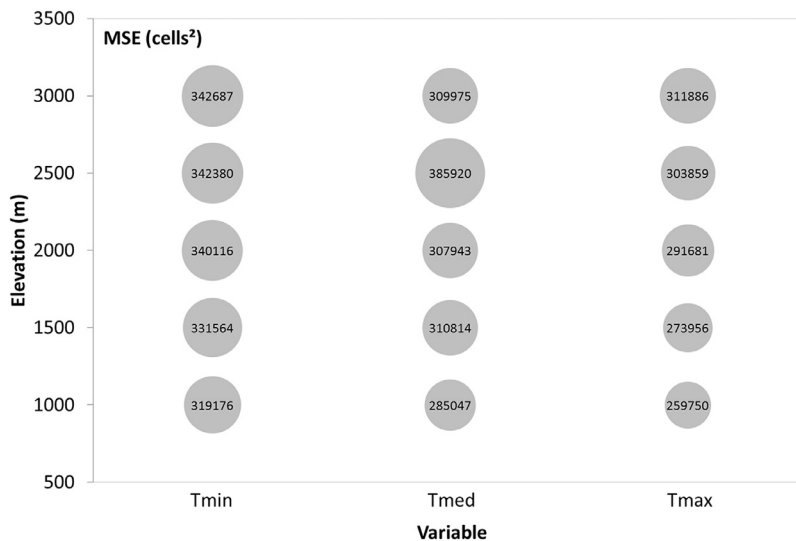


Fig. 2. Mean squared error estimated from the number of errors in cells in the area in the calibration period for numerical experiment A1.

Igúzquiza et al. (2017)) (MSE of 259,750 cells² versus 264,896 cells²), while the validation results were slightly worse (MSE of 457,804 cells² versus 451,212 cells²). The optimal parameters obtained for numerical experiment A1 were ($P_0 = 6.8$; $a = 1140$; $b = 80$; $T_c = 0$; $N_m = 14$) while for numerical experiment AA the results were ($P_0 = 6.8$; $a = 1170$; $b = 80$; $T_c = 0$; $N_m = 14$). Also, this lumped CA approach (numerical experiment A1) has been compared to a logistic regression alternative. For this application, we considered the same explanatory variables as in the CA approach. The logistic regression provided worse results (MSE of 571,406 cells² in the calibration case and 1019,121 cells² in the validation case), underestimating SCA in winter and overestimating SCA in summer. Note that techniques based on regression are performed using the mean of the dependent and independent variables. Therefore they are more sensitive to outliers and less able to capture spatiotemporal variability. In addition, the absence of snow in summer is not properly approached by the regression model. Therefore, the CA methodology provides better approximations than standard regression approaches. For these reasons, the great interest in studying distributed numerical CA solutions is justified.

The variables selected for numerical experiment A1 were used as driving variables for all the distributed numerical experiments (A2, D1, D2, D3). In these distributed numerical experiments, the parameters N_m and T_c from numerical experiment A1 remained fixed, while the remainder were varied, due to the high computational cost of the distributed approaches. Nevertheless, in a subsequent procedure, these parameters were also calibrated for the numerical experiment that had the best results in the first stage. Numerical experiment D2 produced the best results, so a second numerical experiment (D2.1) was performed based on D2 (now varying N_m and T_c and having all other variables remain fixed). This numerical experiment yielded an improvement with respect to the lumped approach developed by Pardo-Igúzquiza et al. (2017) (−6.6% MSE for the calibration period and −10.1% MSE for the validation period). Like Pardo Igúzquiza et al. (2017), in the current study, we tested the possibility of using an absolute temperature threshold instead of a threshold that depends on the previous day (rules a' and b' of the formulation), because it seems to be more reasonable physically (numerical experiments D4 and D4.1), but the approximations obtained were poorer than in Pardo Igúzquiza et al. (2017). Table 1 shows a summary of the CA model numerical experiments performed and their results.

In light of the results, numerical experiment D2.1 was selected to perform the next analysis. In this numerical experiment, the CA parameters were calibrated by minimising the MSE for each climatic zone where the driving variables are defined (Euro-CORDEX grid). For each climatic

zone we calibrated the CA model using the climatological indices of the climatic zone as driving variables for the entire mountain range. We repeated this procedure for all climatic zones in order to obtain distributed parameters. The optimal value of the parameters in the various climatic zones was plotted against the mean elevation of each climatic zone in order to test for possible correlations (Fig. 3).

All parameters, with the exception of T_c , show significant correlations to elevation. Parameters P_0 , a and b increase with elevation, while N_m decreases. When the CA model is applied using these parameters, the best estimated dynamics of daily SCA are obtained. This configuration shows the lowest MSE, which implies the smallest differences between estimated and experimental SCA. In order to assess the performance of the CA model, we calculated the SCA for each day for the entire mountain range and the experimental and estimated datasets. These results are shown in Fig. 4.

In general, extreme snowfall events are underestimated, but general SCA dynamics are captured. We further calculated the number of cells where snow cover exceeded 5, 15, 25 and 35% of days in order to assess the spatial distribution of snowfall. Fig. 5 shows that experimental and estimated SCA have a very similar pattern.

Thus, we demonstrate that the CA model applied is able to reproduce the spatial dynamics of SCA for the calibration period. In the same way, the validation results are shown in Figs. 6 and 7. Again, the temporal SCA dynamics are captured but extreme snowfall events are underestimated.

We have also compared the estimates to experimental data cell by cell for the calibration and validation data, obtaining the failure probability of the CA model in two situations: errors when the cell is covered, and when there is no snow (see Fig. 8). Note that the model is more likely to fail when the cell is covered by snow ($S(i, j, t) = 1$) at lower elevations where snow dynamics change more quickly. From the point of view of water resources quantification, these errors are not very important because at those elevations snow thickness is lower. With respect to spatial distribution, the probability of failure is similar for the two periods and the two cases (snow covered or snow-free).

Furthermore, we have evaluated the uncertainty of parameters using the procedure explained in Section 2 (Eq. (1)) for the lumped CA model. The standard deviations of the calibrated parameters are shown in Table 2. The uncertainty of the CA model outputs has been quantified by considering the MSE of the calibration period as explained in Section 2. The experimental data and the uncertainty interval defined by estimates $\pm$ standard deviations of SCA are shown in Fig. 9. For the case study, on 69.1% of the days the experimental data are within the uncer-

Table 1
Summary of the CA numerical experiments carried out in this study.

Numerical experiments	Series	Parameters	Calibration					Results of calibration		Results of validation	
			Tested Variables	Elevation (m)	Minimization	Parameters	Temperature threshold	ME (cells)	MSE (cells ²)	ME (cells)	MSE (cells ²)
AA*	Lumped	Lumped	- P and T_{min} - P and T_{med} - P and T_{max}	1000,1500, 2000, 2500 and 3000	For the entire mountain range	Varying one and fixing the rest	Relative to $t-1$	62	264,896	-49	451,212
AB*	Lumped	Lumped	- P and T_{min} - P and T_{med} - P and T_{max}	1000,1500, 2000, 2500 and 3000	For the entire mountain range	Varying one and fixing the rest	Absolute		308,760		580,121
A1	Lumped	Lumped	- P and T_{min} - P and T_{med} - P and T_{max}	1000,1500, 2000, 2500 and 3000	For the entire mountain range	Varying all simultaneously	Relative to $t-1$	9	259,750	-115	457,804
A2	Distributed (the series of each climatic zone are the driving variables for that climatic zone)	Lumped	- P and T_{max} (from A1)	1000 (from A1)	For the entire mountain range	Varying a, b, P_0 Fixing N_m, T_c (from A1)	Relative to $t-1$	-23	288,672	-128	467,104
D1	Distributed (the series of each climatic zone are the driving variables for the whole mountain range)	Distributed	- P and T_{max} (from A1)	1000 (from A1)	For the entire mountain range	Varying a, b, P_0 Fixing N_m, T_c (from A1)	Relative to $t-1$	11	260,778	-150	422,191
D2	Distributed (the series of each climatic zone are the driving variables for the whole mountain range)	Distributed	- P and T_{max} (from A1)	1000 (from A1)	For each climatic zone	Varying a, b, P_0 Fixing N_m, T_c (from A1)	Relative to $t-1$	8	258,764	-185	412,152
D2.1	Distributed (the series of each climatic zone are the driving variables for the whole mountain range)	Distributed	- P and T_{max} (from A1)	1000 (from A1)	For each climatic zone	Varying N_m, T_c Fixing a, b, P_0 (from D2)	Relative to $t-1$	31	247,473	-129	405,806
D3	Distributed (the series of each climatic zone are the driving variables for that zone)	Distributed	- P and T_{max} (from A1)	1000 (from A1)	For each climatic zone	Varying a, b, P_0 Fixing N_m, T_c (from A1)	Relative to $t-1$	-9	259,539	-198	424,324
D4	Distributed (the series of each climatic zone are the driving variables for the whole mountain range)	Distributed	- P and T_{max} (from A1)	1000 (from A1)	For each climatic zone	Varying a, b, P_0 Fixing N_m, T_c (from AA)	Absolute	41	292,164	-285	575,346
D4.1	Distributed (the series of each climatic zone are the driving variables for the whole mountain range)	Distributed	- P and T_{max} (from A1)	1000 (from A1)	For each climatic zone	Varying N_m, T_c Fixing a, b, P_0 (from D4)	Absolute	35	285,639	-296	609,799

* From Pardo-Igúzquiza et al. (2017).

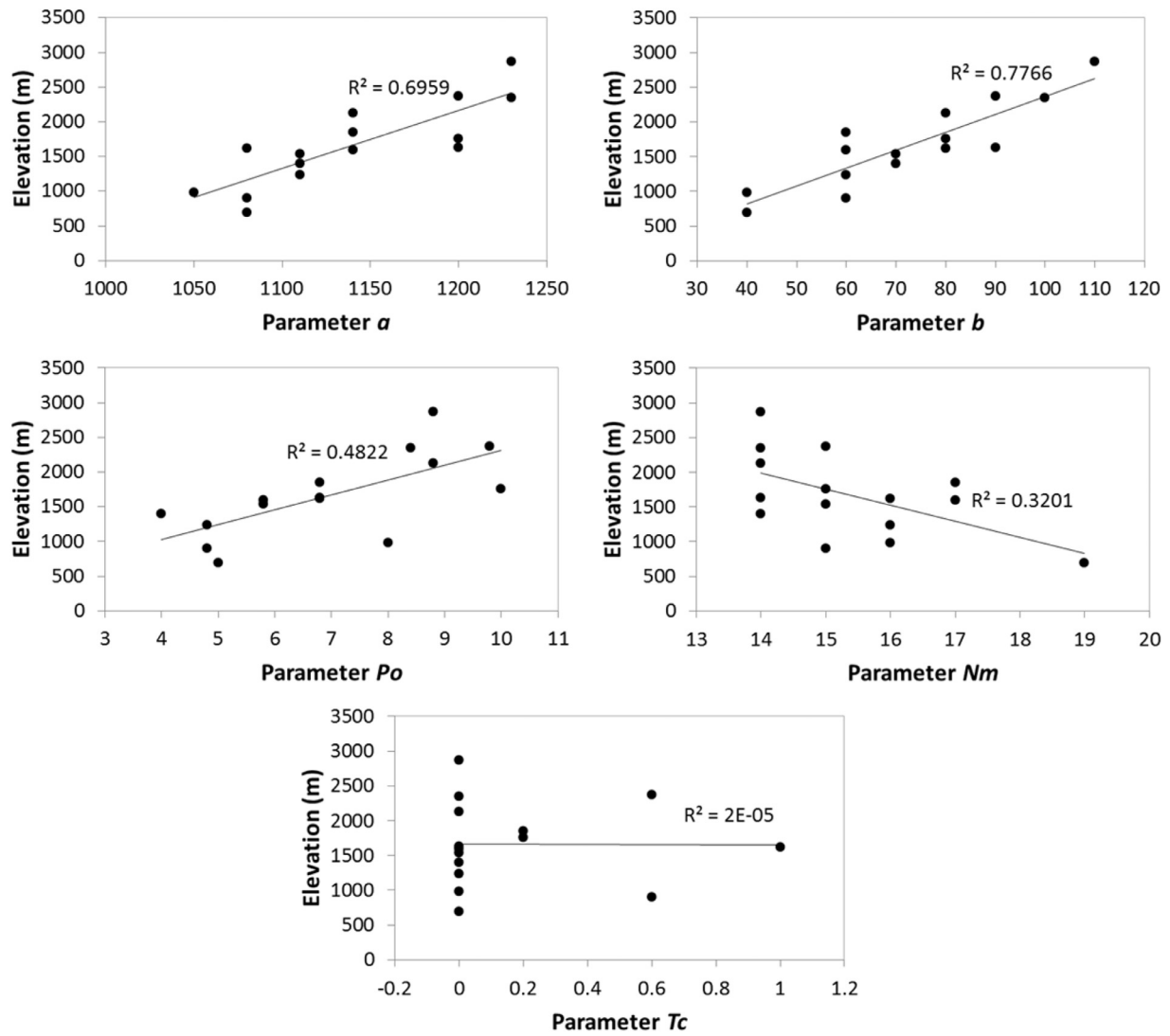


Fig. 3. Value of the calibrated parameters in the various climatic zones compared to the mean elevation of each climatic zone.

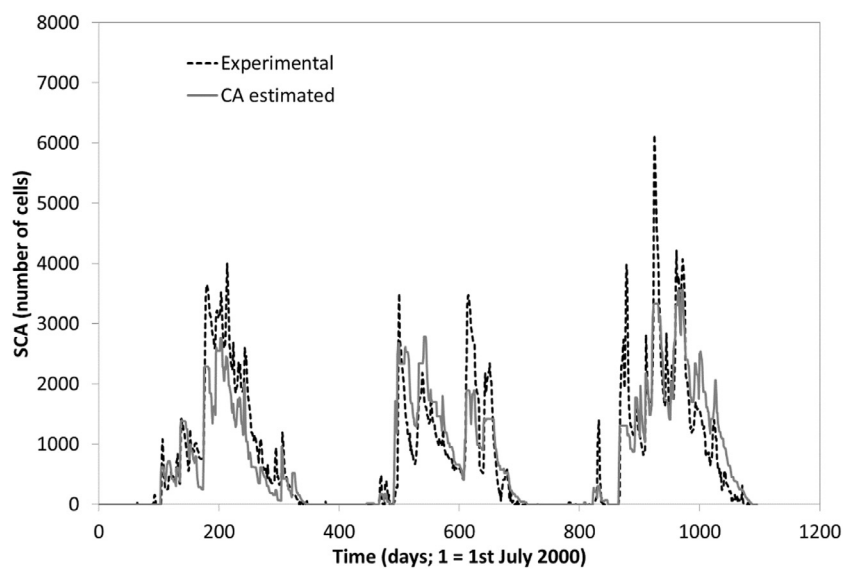


Fig. 4. Experimental SCA and SCA estimated by the calibrated CA model over the calibration period.

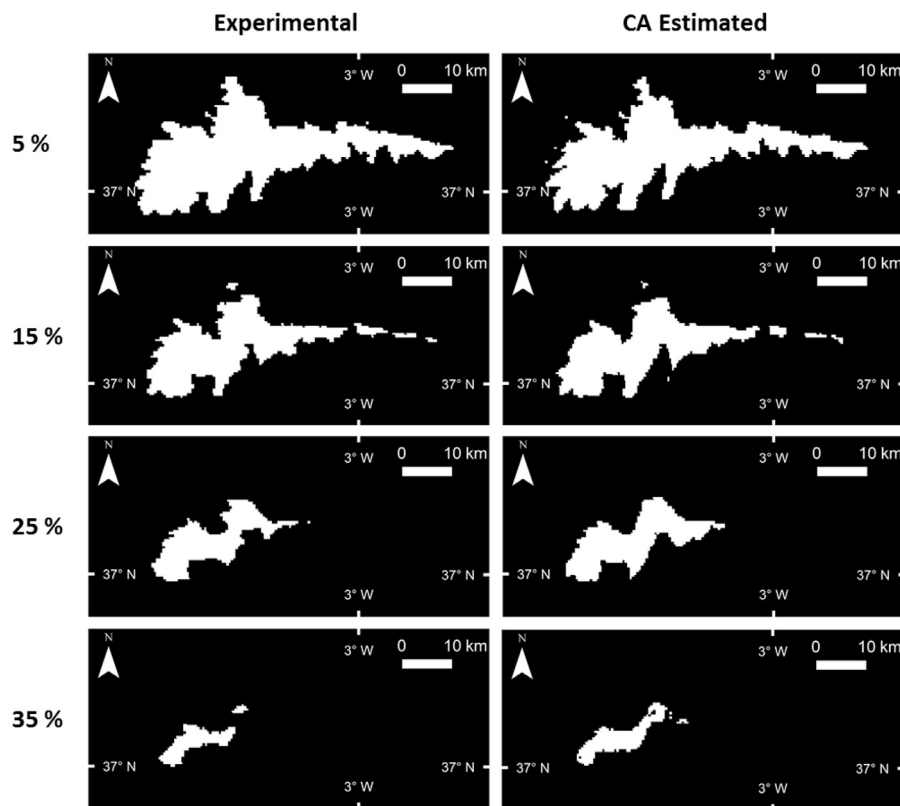


Fig. 5. Cells where snow cover exceeds 5, 15, 25 and 35% of days for experimental and estimated SCA using the calibrated cellular automata model over the calibration period.

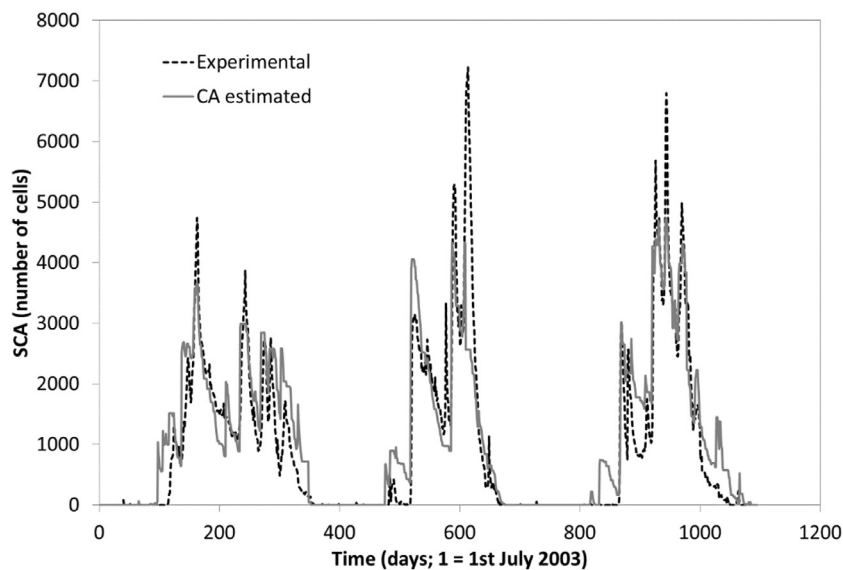


Fig. 6. Experimental SCA and SCA estimated by the calibrated CA model for the validation period.

Table 2

Optimal values of parameters and standard deviations for the lumped CA model.

Parameter	Optimal value	σ
P_0	6.8 mm	0.20 mm
a	1140	34.35
b	80	2.77
T_c	0 °C	0.10 °
N_m	14	0.18

tainty interval. This value is similar to the theoretical value assuming a Gaussian distribution, represented by 68%.

As noted in the methodology section, the climate change information used to generate potential future scenarios can be taken from the RCM. In our case study, we used nine RCMs from the [CORDEX PROJECT \(2013\)](#). We selected the most pessimistic emissions scenario of the project, Representative Concentration Pathways 8.5 (RCP8.5). [Table 3](#) shows the RCMs used and the GCM in which they are nested.

We considered the historical period 1971–2000 and the future period 2071–2100 to perform the statistical transformations used to generate the potential future scenarios. The method was systematically applied

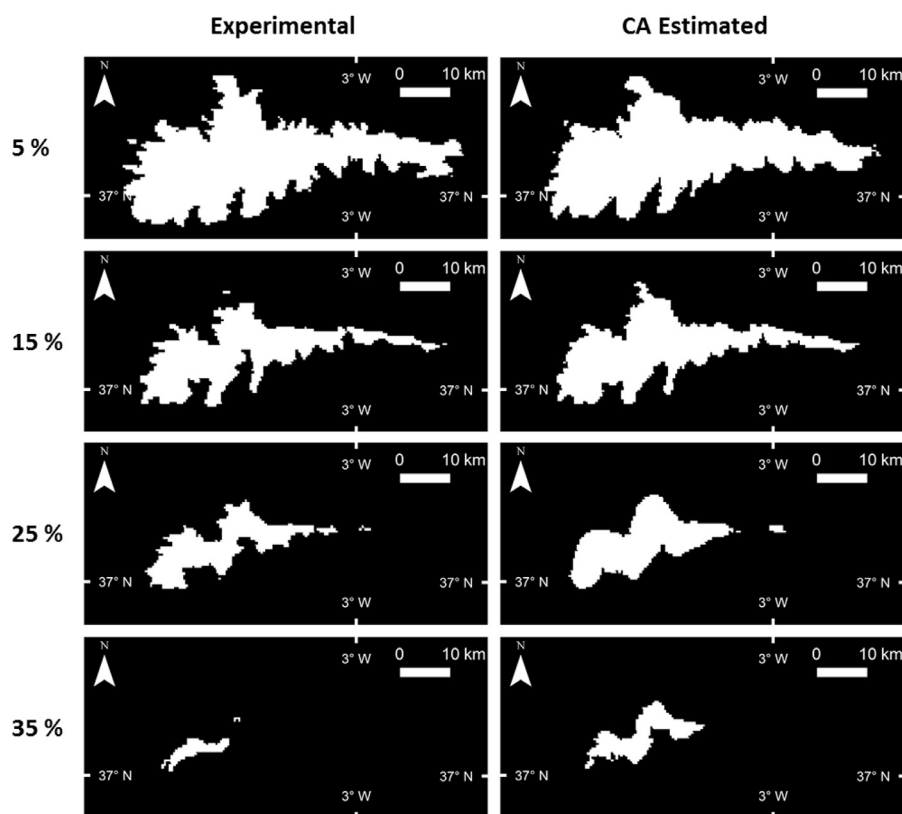


Fig. 7. Cells where snow cover exceeds 5, 15, 25 and 35% of days for the experimental and estimated SCA using the calibrated CA model for the validation period.

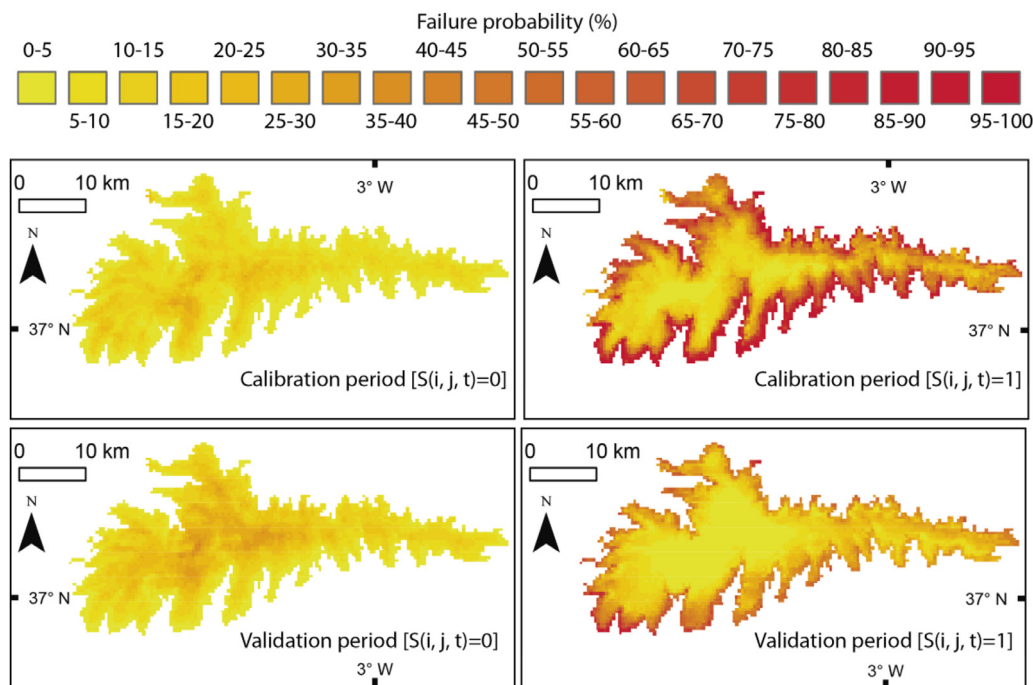


Fig. 8. Failure probability of the CA model in the calibration and validation periods.

to all cells of the Euro-Cordex grid inside the study area to obtain the future precipitation and maximum temperature series (the driving variables selected for the CA model). We considered two precipitation and temperature climate change scenarios, depending on which approach was employed – delta change (E1) or bias correction (E2). These two scenarios, E1 and E2, are equi-feasible solutions obtained from the nine RCMs considered. These two future scenarios are used as the driving

variables for the calibrated CA model in order to obtain potential future scenarios of snow cover area due to climate change. An example of the precipitation and temperature time series generated for a particular cell is presented in Fig. 10.

There is a significant reduction in precipitation and a significant increase in temperature. The means of the series generated for the two scenarios are similar in the case of precipitation and the same in the

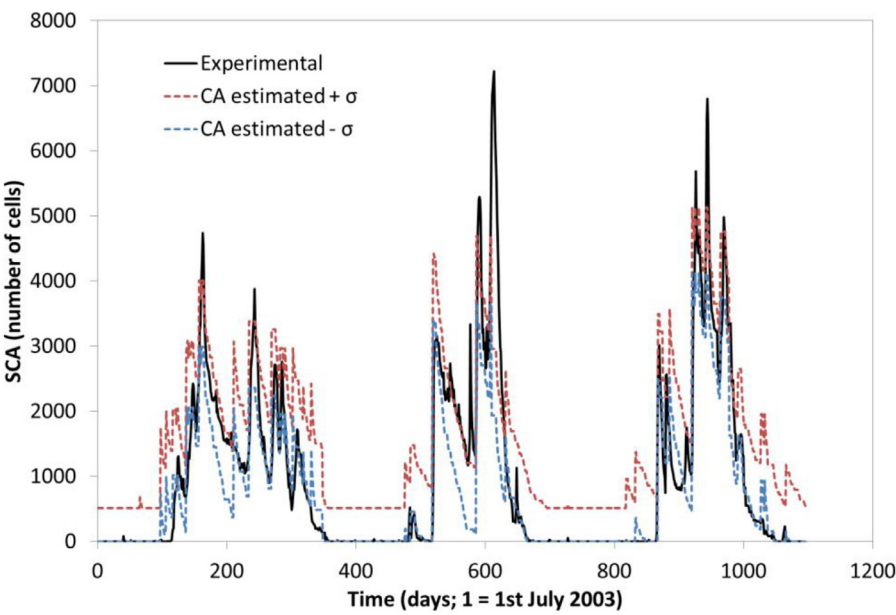


Fig. 9. Experimental and estimates $\pm$ standard deviation of SCA using lumped CA model for the validation period.

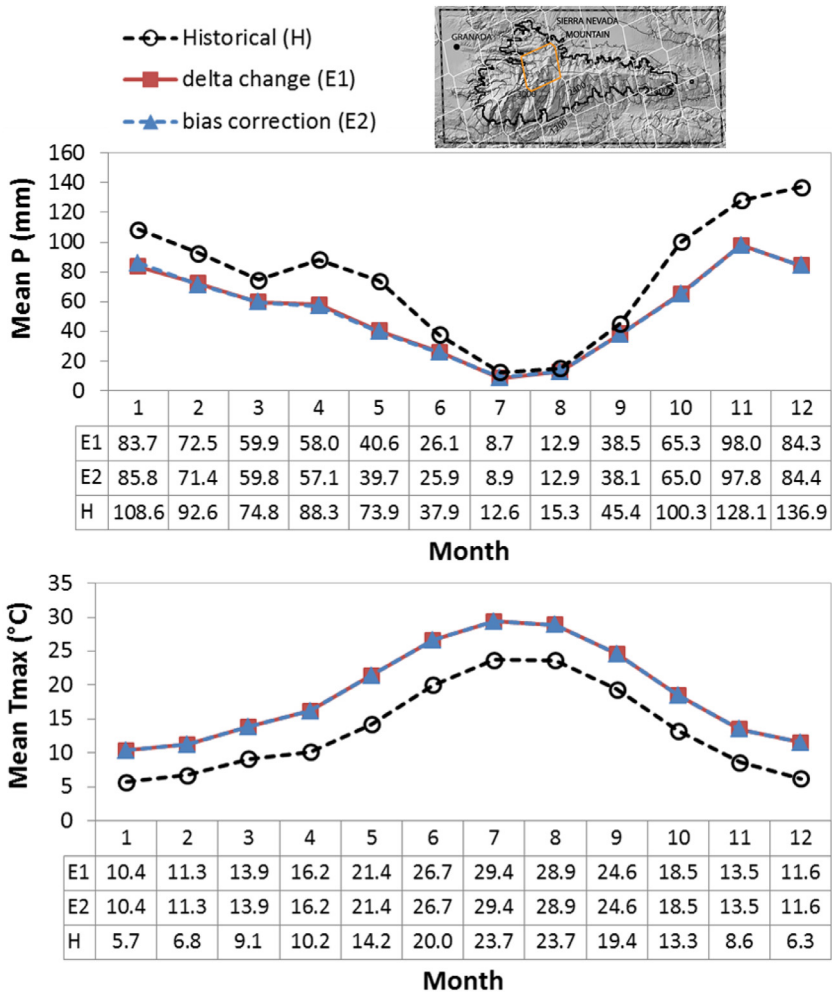


Fig. 10. Historical and ensemble of future precipitation and maximum temperature series for the bias correction and delta change approaches for a given climatic zone.

Table 3
Regional Climatic Models (RCMs) and General Circulation Models (GCMs) considered for simulations.

RCMs	GCMs			
	CNRM-CM5	EC-EARTH	MPI-ESM-LR	IPSL-CM5A-MR
CCLM4-8-17	X	X	X	
RCA4	X	X	X	
HIRHAM5		X		
RACMO22E		X		
WRF331F				X

case of maximum temperature. Theoretically, the means must be the same in the two scenarios, even though the time series are different, so that the two scenarios have different behaviour when they are fed into the CA model. However, in the case of precipitation, the small differences are due to negative values generated in the statistical process that are corrected to zero.

In order to evaluate potential climate change spatially, we calculated the relative changes in precipitation and maximum temperature for all cells, plotting them with respect to elevation (see Fig. 11).

Fig. 11 shows that climate change leads to an increase in maximum temperature and a decrease in precipitation with elevation. So, in this alpine system the potential climate change will be greater in the case

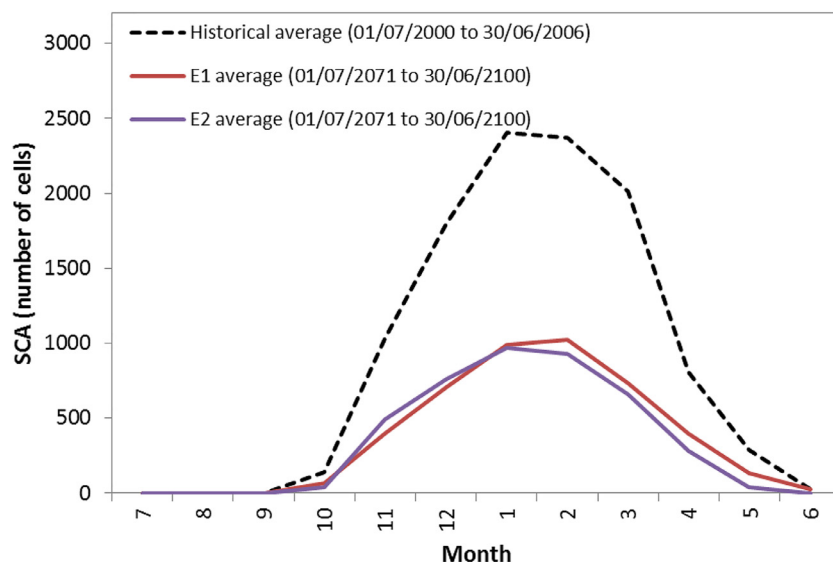
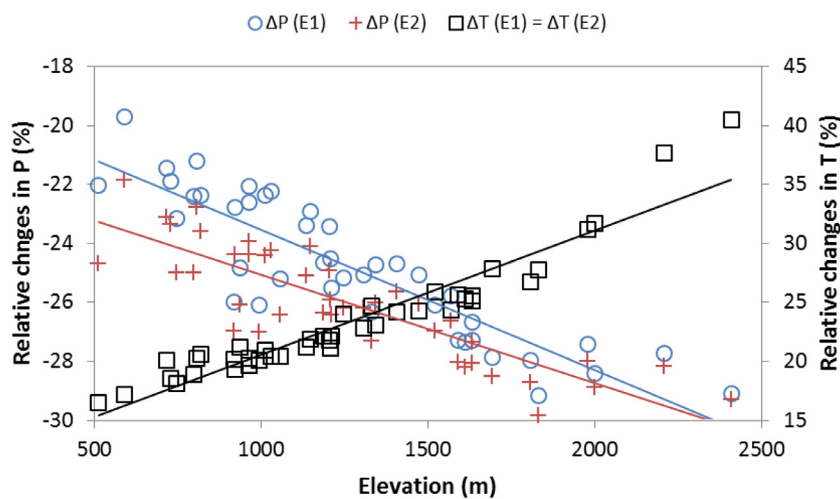


Table 4
Potential relative changes in SCA for the two scenarios considered.

Month	Relative changes in SCA (%)	
	Scenario E1	Scenario E2
October	−50.8	−69.7
November	−61.4	−52.5
December	−60.9	−57.8
January	−58.9	−59.8
February	−57.0	−60.8
March	−63.6	−67.2
April	−51.3	−65.3
May	−54.8	−86.6

of temperature and smaller in the case of precipitation for higher elevations.

The CA model was fed with the series generated for the two scenarios. This yielded significant reductions in SCA (59.0% for E1 and 61.7% for E2). The size of the reduction depends on the month (Table 4).

Figs. 12 and 13 shows the mean monthly and daily historical and future SCA, respectively. Graphically, we verified that potential reductions in SCA are highly significant. Fig. 14 shows the cells with snow cover on more than 5, 15, 25 and 35% of days for the histori-

Fig. 11. Relative changes in precipitation and temperature with respect to the elevation of each climatic zone.

Fig. 12. Historical and future monthly estimated SCA using the calibrated cellular automata model.

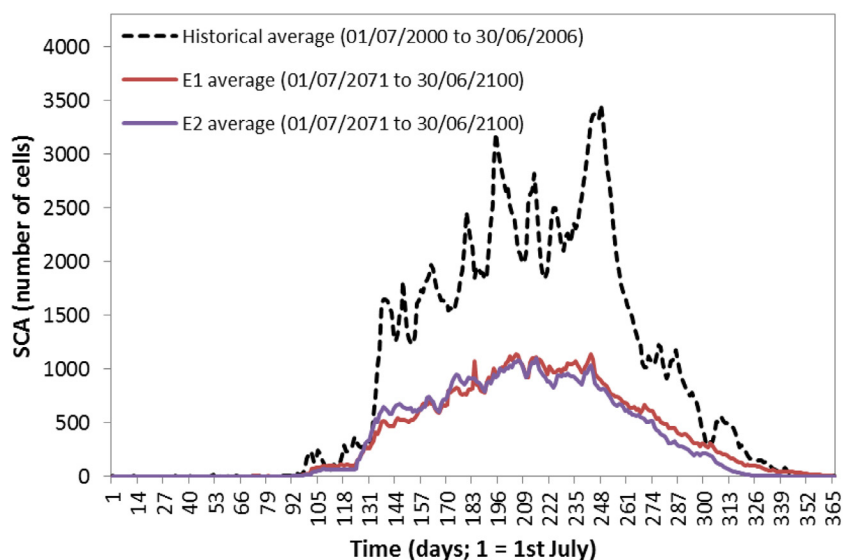


Fig. 13. Historical and future daily estimated SCA using the calibrated cellular automata model.

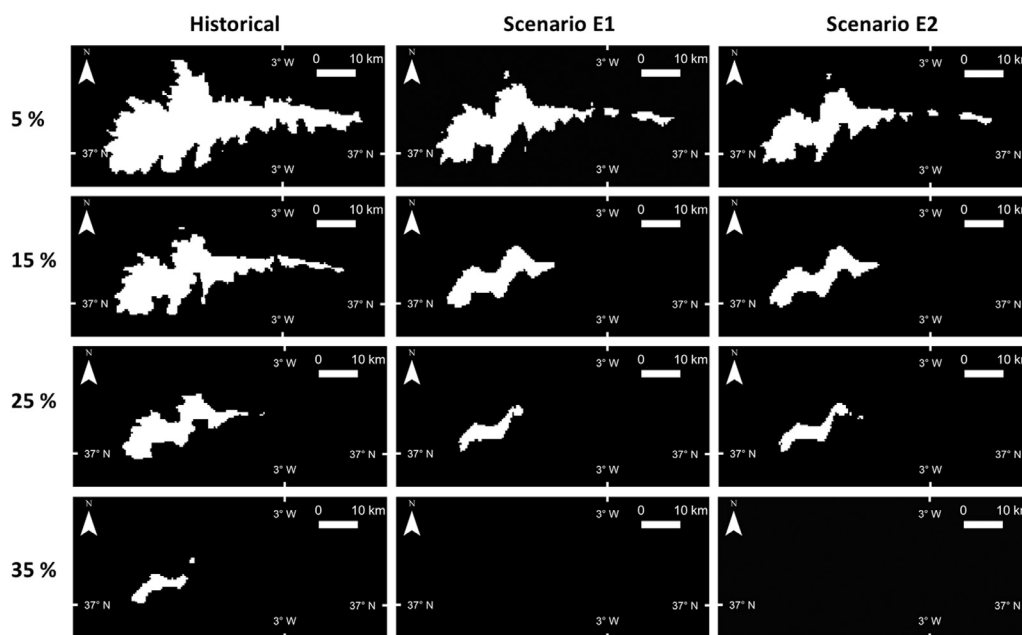


Fig. 14. Cells with snow cover for more than 5, 15, 25 and 35% of days for the historical and future scenarios.

cal and future potential scenarios; again, the potential reductions are significant.

4. Limitations and future research

It should be noted that when hydrological models, especially those defined at a regional scale covering an extensive area with heterogeneous conditions (as in our case), are employed to simulate conditions and that are very different from those used to calibrate and validate the model, uncertainty in the assessment increases. For this reason, all the models should be validated again when new information is available. This occurs even with physical hydrological models (e.g. groundwater flow models, rainfall-runoff models, etc.). Our model, although it is not based on such physical models, provides coherent solutions with the capability to predict very extreme conditions; for example, if snow is not present, it does not show any values of SCA.

Nevertheless, as explained above, in all models uncertainty grows when they are used to simulate very different conditions. The patterns and variability of future climate conditions may be considerably differ-

ent from the historical/current climate data used to calibrate and validate the model's parameters (the model's rules in our approach) (IPCC, 2007, 2013). However, despite the inevitable uncertainty in predicting the impact of climate change (an uncertainty that also exists in many other aspects analysed by the scientific community, both within physical and non-physical processes, and which is also inherent to the definition of potential climate change scenarios), there is a clear need to provide a quantitative assessment of potential hydrological impacts. This will allow scientists to rationally evaluate potential adaptation strategies for maintaining sustainable management of water resources systems, which may be very vulnerable to climate change. Due to the importance to society of understanding the potential impacts of climate change, although there may be uncertainties involved in this impact assessment, scientific production on this issue is very relevant (e.g., Brown and Mote, 2009; Vorosmarty et al., 2000).

In this work we assume a steady LULC in historical and future scenarios in order to perform a sensitivity analysis of the SCA dynamics to potential future climate scenarios. Therefore, representative SCA results can be provided for long-term future climate periods if we assume

that LULC will remain quite similar to its historical data, or that the changes do not have an important influence on the snow dynamic. The CA model has been calibrated and validated with P and T time series from recent years and it only requires P and T time series in order to assess the impact on the future evolution of SCA. Suppose we take the P and T time series projected for the year 2100. There will be, on average, less rainfall and higher temperatures. Suppose that these time series are taken to be the record from a recent abnormally dry and hot year. We would think that the output of the model is valid for this recent year, although we are using the projections for the year 2100. Thus, as long as we assume that the calibration is robust in accordance with the validation performed, and make the hypothesis that the parameters (rules, in our approach) will remain invariable in the future, as they depend on P and T only (because topographic parameters may be considered constant at a timescale of one hundred years), the use of CA will be valid for addressing SCA dynamics in the future. The spatial change in the global circulation of the atmosphere has already been taken into account in the P and T time series projections for the future.

New research would be needed to use the same CA model to study a historical period with significant LULC changes, or to simulate potential future impacts that also include future LULC changes. Most likely, such models would need to include other spatial variables influenced by LULC in the rules.

Additionally, different parameter sets can lead to similar responses in the SCA dynamics (principle of equifinality). The analysis of parameters in this deterministic model cannot be used to draw conclusions about the factors that influence snow dynamics. As a future line of research, a new approach would be required to perform a more complete analysis of the factors that influence SCA, combining stochastic and physical-based models.

5. Conclusions

A CA model to estimate SCA has been calibrated and validated with good results for the Sierra Nevada mountain range (southern Spain). We implemented several lumped and distributed numerical experiments (varying the driving variables, algorithm parameters, minimisation procedure, search for optimal parameters and temperature) based on a lumped CA model developed by Pardo-Igúzquiza et al. (2017). The best implementation (numerical experiment D2.1) reduced the MSE by 6.6% and 10.1% in the calibration and validation periods, respectively, compared to the initial lumped CA model. Subsequently, we used this best CA model numerical experiment to assess the impacts of climate change on snow cover dynamics using future precipitation and temperature scenarios as driving variables.

When the relative changes in the future precipitation and maximum temperature time series generated (with respect to the historical series) are plotted against mean elevation in each grid, we conclude that, in this alpine case study, potential climate change at higher altitudes will result in higher temperatures and lower precipitation.

The future series generated was used as an input for the calibrated CA model, leading to the worrying result that there will be a drastic reduction in snow cover area in the future. Using the future precipitation and temperature scenarios as driving variables for the period 2071–2100, we obtain a significant reduction in snow cover area using the calibrated CA model (59.0% for E1 and 61.7% for E2).

Thus, the distributed CA developed is proved to be a useful tool for predicting the future evolution of snowpack. This tool can be applied to various management tasks, including water resources management, operational river forecasts and landscape management.

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